The Application of Eye Movement Biometrics in the Automated Detection of Mild Traumatic Brain Injury

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Abstract
This paper presents a pilot study for the automated detection of mild traumatic brain injury (mTBI) via the application of eye movement biometrics. Biometric feature vectors from multiple paradigms are evaluated for their ability to differentiate subjects diagnosed with mTBI from healthy subjects within a small subject pool. Supervised and unsupervised machine learning techniques were applied to the problem, with preliminary results indicating a potential 100% classification accuracy from a supervised learning technique and 89% classification accuracy from an unsupervised technique.

ACM Classification Keywords
I.2.1. Artificial Intelligence: Applications and Expert Systems – Medicine and science; J.3. Computer Applications: Life and Medical Sciences – Health.

Introduction
Traumatic brain injury (TBI) is defined by the American Congress of Rehabilitation Medicine [11] as any physical trauma that results in memory loss, altered mental state, loss of consciousness, or focal neurological deficits. TBI is classified as "mild" (mTBI) when loss of consciousness does not exceed 30 minutes, Glasgow Coma Scale does not exceed 13-15 after 30 minutes, and memory loss does not extend beyond a 24-hour period.

According to reports from the Centers for Disease Control and Prevention [4], approximately 1.7 million people are diagnosed with TBI each year in the United States, of which nearly 75% (or 1.3 million) are incidences of mTBI. This does not account for the undiagnosed occurrences of mTBI that are thought to exceed 25% of the reported figure, or nearly 425,000 undiagnosed cases per year.

Each year there are approximately 52,000 TBI-related deaths in the United States, accounting for roughly one-third (30.5%) of all injury-related deaths [4]. mTBI increases the risk of TBI [5], and can cause neurological disorders which persist years after injury [16], affecting thought, behavior, and emotion, producing physical symptoms such as fatigue, nausea, vertigo, headache, lethargy, and blurred vision [11].

The ability to diagnose mTBI is especially important for active military personnel and professional sports players, for whom it is common to sustain repeated head trauma, the severity of which can range from inconsequential to severe. Unfortunately, there are few quantitative measures by which to assess the presence and severity of TBI, with health care professionals often employing qualitative guidelines to assist in diagnosis.

Eye movements have been utilized by physicians to diagnose many common neurological disorders for decades [17]. Due to the integrated nature of the oculomotor plant and brainstem control [3], neurological disorders are often expressed through abnormalities in human eye movements [17].

Previous Research

In 1995, Hellerstein et al. conducted a qualitative study on the effects of mTBI on patient vision. Within an age-matched subject pool of 16 mTBI patients and 16 healthy controls, it was found that subjects diagnosed with mTBI exhibited significant abnormalities in vergence and smooth pursuit eye movements.

In 2004, Heiteger et al. conducted a quantitative study on the effects of mTBI exhibited in reflexive, anti-, and memory-guided saccades. In general, mTBI patients displayed significantly less spatial accuracy, longer saccadic latency, and more target errors than matched (age, gender, education) control subjects within a population of 60 participants. This was followed, in 2006, by a longitudinal study [8] of the recovery of oculomotor function in mTBI patients, which documented noticeable deficits up to a year after injury.

In 2007, Drew et al. conducted a quantitative study on the effects of mTBI on saccades in a gap-saccade task. With a matched (age, gender, education) subject pool of 20 mTBI patients and 20 healthy controls, it was found that saccadic latency was significantly greater for mTBI patients immediately following injury, but recovered quickly, with no statistically significant difference after 1 week of recovery.

In 2011, Ciuffreda et al. published a list of diagnostic oculomotor parameters identified from over a decade of clinical research. Results indicated that mTBI patients exhibit specific types of anomalies with respect to vergence, versional, and accommodative eye movements.

Algorithm *Heuristic*
for *i* ← 1 to *Eye movement recording count*
  do *mTBI* ← 0
    if *Fixation Quantiative Score < Average*
    then *mTBI* ← *mTBI* + 1/7
    if *Fixation Count < Average*
    then *mTBI* ← *mTBI* + 1/7
    if *Multi-Corrected Undershoot < Average*
    then *mTBI* ← *mTBI* + 1/7
    if *Fixation Duration > Average*
    then *mTBI* ← *mTBI* + 1/7
    if *Saccade Amplitude > Average*
    then *mTBI* ← *mTBI* + 1/7
    if *Simple Overshoot > Average*
    then *mTBI* ← *mTBI* + 1/7
    if *Activation-Time Constant > Average*
    then *mTBI* ← *mTBI* + 1/7

Figure 1: Unsupervised learning technique.

Motivation & Hypothesis
While there is substantial evidence that mTBI causes measurable deficits in oculomotor behavior [1, 2, 6-8], there has been little attempt to develop automated diagnostic tools, and many aspects of the visual system remain unstudied, despite the accuracy and affordability of modern eye tracking systems [3]. Over the past decade, an emergent sub-field of biometrics has grown around the idea that the unique properties of the oculomotor control system can be interpreted from the measurable properties of eye movements [9, 10, 14, 15]. Therefore, we hypothesize that eye movement biometrics will exhibit patterns that may assist in the diagnosis of mTBI, providing an automated framework with which to reduce the workload of physicians.

Methodology

High-resolution recordings from an openly available eye movement database [12], were utilized to allow for the reproducibility of the considered experiments, with collection methodology presented in the following section.

Apparatus & Software
Binocular eye movements were recorded using the EyeLink 1000 eye tracking system, with accuracy of 0.25° – 0.5°, resolution of 0.01° RMS, and sampling rate of 1000 Hz. The recordings exhibited an average calibration accuracy of 0.8° (±0.6), with an average data loss of 2.3% (±3.9). The stimulus was presented on a flat screen monitor positioned at distance of 685 mm from the subject, with dimensions of 640×400 mm, and resolution of 2560×1600 pixels. A chin rest was employed to improve stability.

Participants
Eye movement recordings were collected for 32 subjects (26 males, 6 females), ages 18 – 40 with an average age of 23 (±5.4). Of these, 2 subjects had recently sustained head injuries resulting in mTBI; one subject was recorded the day after the injury and the other was recorded 111 days after the injury. Both mTBI subjects and 27 of the healthy subjects performed 4 recordings per stimulus, and 3 of the healthy subjects performed 2 recordings per stimulus. Subjects were given a 20-minute break between the 1st and 2nd recording session, with 2 weeks between the 2nd and 3rd recording session, and 20 minutes between the 3rd and 4th recording session. mTBI injuries were self-reported by subjects after data collection, and data collection procedures were approved by IRB committee.

Procedure
Eye movement recordings were generated for two stimuli, designed to evoke fixed-amplitude horizontal (30°) and vertical saccades (20°), at regular 1-second intervals. For both stimuli, a small white dot jumped back and forth on a plain black background, eliciting a saccade with each jump. The amplitude was chosen due to screen constraints and complications associated with separating low-amplitude saccades (less than 1°). Subjects were instructed to follow the white dot with their eyes, with 100 saccades elicited per recording. For each recording session, the horizontal and vertical stimuli were presented approximately 2 minutes apart.

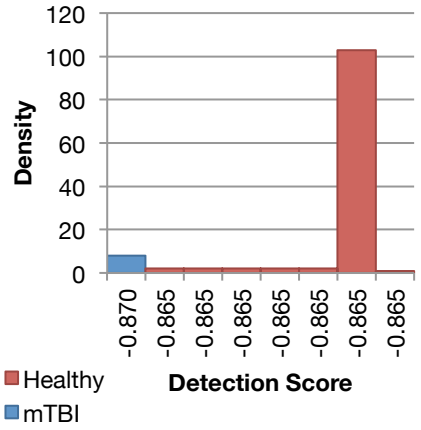

Figure 2: Supervised score histogram.

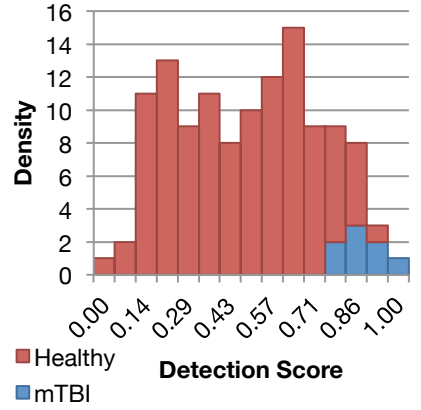

Figure 3: Unsupervised score histogram.

Biometric feature vectors and standardized quality measures [13] were extracted from each recording according to the CEM-P [9], CEM-B [10], COB [14], and OPC [15] eye movement biometric techniques. CEM techniques are related to the conscious behavior of the human visual system, COB techniques are related to subconscious corrective behavior of the human visual system, and OPC techniques are related to the physical structure of the oculomotor plant. Average feature values were utilized in the case of CEM-B and OPC, which operate by comparing the distribution of features. Feature vectors were examined manually in an attempt to identify patterns or clustering that might be utilized to distinguish between mTBI and healthy recordings.

Fixation quantitative score represents the ratio of measured fixation points against the total number of stimuli. Fixation count is the total number of measured fixations. Multi-corrected undershoot is the number of saccades which undershoot the target stimulus and are followed by more than one corrective saccade. Fixation duration is the average fixation duration across the recording. Vectorial saccade amplitude represents the average Euclidean distance covered by each saccade. Simple overshoot is the number of saccades that overshoot the target stimulus and are not followed by corrective saccades. The agonist muscle activation-time constant is a constant in the mathematical model of the oculomotor plant responsible for transforming the neuronal control signal into contractile force over time, with respect to the agonist extraocular muscle.

During manual examination of the biometric feature vectors, it was noted that (in both horizontal and vertical stimulus recordings) there was a strong tendency for subjects with mTBI to exhibit: lower than average values of the fixation quantitative score, fixation count, and multi-corrected undershoot; and higher than average values of fixation duration, vectorial saccade amplitude, simple overshoot, and the agonist muscle activation-time constant.

After potentially relevant biomarkers were established, two algorithms were implemented to assess the accuracy of mTBI detection with supervised and unsupervised learning techniques. The supervised learning technique utilized support vector regression with a radial basis function (gamma = 1) applied to the 7 features identified during manual examination. Leave-one-out cross-validation was performed to obtain mTBI detection scores for each recording. The unsupervised learning technique utilized a heuristic method, given in Figure 1, in which the probability of mTBI was estimated as the percent of features above or below average.

Results

For each recording session mTBI detection scores were averaged between the horizontal and vertical stimuli, regression values were binned, and simple thresholding was applied to the mTBI detection scores generated by each algorithm to calculate confusion matrices, sensitivity, specificity, and accuracy.

Detection Scores

mTBI detection scores are presented as a histogram in Figures 2 and 3. Based on the distribution of detection scores, arbitrary thresholding was employed to measure the achievable accuracy. For the supervised technique, recordings with detection score ≤ -0.870 were classified as mTBI. For the unsupervised technique, recordings with detection score ≥ 0.79 were classified as mTBI.

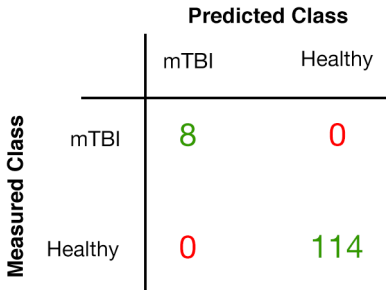

Figure 4: Supervised confusion matrix.

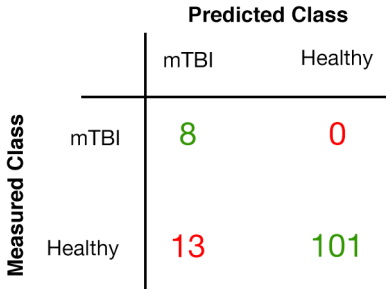

Figure 5: Unsupervised confusion matrix.

Classification Accuracy

Confusion matrices are presented in Figures 4 and 5. For the supervised technique, these results indicate a potential 100% specificity, 100% sensitivity, and 100% accuracy, and for the unsupervised technique, 89% specificity, 100% sensitivity, and 89% accuracy.

Discussion

During our manual examination of biometric feature vectors, we also attempted to identify features that might exhibit potential recovery patterns; that is, biometric features in mTBI subjects that changed linearly and consistently over time. While several features were noted during examination, there was no crossover in the biometric features noted for the horizontal and vertical stimulus recordings. This suggests rather strongly that the patterns exhibited by these features were due to random chance.

Further, in our initial investigations of these techniques, the considered experiments were repeated to include all available biometric features. The inclusion of these extraneous features reduced the overall accuracy of these techniques, enforcing the need for dimensionality reduction, and confirming that mTBI does not affect all aspects of the oculomotor system evenly.

The results of these experiments are encouraging, and suggest rather strongly that it is possible to detect mTBI using automated eye movement techniques. Though the supervised technique required training data and, subsequently, cross-validation to reduce the likelihood of overfitting, it was able to achieve linear separability between mTBI and healthy subjects. Similarly, while the unsupervised technique was unable to achieve linear separability, the achievable accuracy was relatively high, resulting in a small amount of false positives that could easily be identified during post-diagnostic screening.

At the same time, it is important to note that the sample size in this pilot study is too small to draw specific conclusions. It is entirely possible that the separability of mTBI from healthy subjects is due to unknown or unmeasurable factors. Despite this, the accuracy achieved by these techniques is sufficient to warrant further study, and future research will likely see a substantial increase in the size of the considered subject pool, in addition to algorithmic improvements.

Conclusion

This paper has presented a pilot study for the automated detection of mild traumatic brain injury (mTBI) via the application of eye movement biometrics. Biometric feature vectors from multiple paradigms were evaluated for their ability to differentiate subjects diagnosed with mTBI from healthy subjects within a small subject pool. It was found that the fixation quantitative score, fixation count, fixation duration, vectorial saccade amplitude, simple overshoot, multi-corrected undershoot, and the agonist muscle activation-time constant exhibited obvious clustering in mTBI patients.

Supervised and unsupervised machine learning techniques were applied to the classification problem, based on support vector machine and heuristic algorithms. The supervised technique achieved a potential 0% false positive rate, 0% false negative rate, and 100% accuracy, while the unsupervised technique achieved a potential 11% false positive rate, 0% false negative rate, and 89% accuracy. The accuracy achieved by these techniques is encouraging and warrants further study.

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